AI for Accurate, Fast, and Robust Plant Damage Assessment

Experiential Introduction to AI and Ecology
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Relevance

Plants are considered invasive when they are not native to an environment and can cause environmental, economic, or human health damage [2]. Ocean archipelagos, such as Hawaii, are considered particularly vulnerable to invasive plants due to their isolated evolutionary history [17, 11]. The lack of natural enemies in a new environment, such as herbivores or pathogens, is believed to give invasive plants a comparative advantage over natives occupying similar niches, a process called the enemy release hypothesis [9, 20]. Biocontrols, the introduction of organisms that consume or parasitize the invasive plant in its native range, have the potential to be an effective and sustainable mitigation strategy. However, outside of agricultural settings, assessing the effectiveness and ecological impact of biocontrol agents is a challenge.

Clidemia hirta (syn. *Miconia crenata*) is shade tolerant perennial shrub native to Central and South America and is thought to have been introduced to Hawaii in the early 20th century [13]. The plant is highly adapted to different environmental conditions and can quickly out-compete native vegetation by smothering access to sunlight and soil and forming large mono-typical patches [3, 18]. Their rapid growth, high seed production, and lack of natural enemies in Hawaii are considered the main factors leading to its spread [7]. At least since the 1950s, several biocontrol agents have been introduced to Hawaii in attempts to reduce the impacts of *Clidemia*, but quantitative assessment of their sucess has been limited [6]. Of particular relevance are different insect species, whose larval stages consume the leaves of *C. hirta*: (i) *Liothrips urichi* a thrips species that forms concentrated areas of damage and discoloration on *Cledemia* leaves; (ii) *Antiblemma acclinalis* a moth species whose young larva make characteristic rectangular holes and late instars eat large irregular portions of the leaves; and (iii) *Lius poseidon* a leaf-mining beetle species. These have been introduced to the Hawaii island, but lack rigorous evaluation of their effects [12].

Leaf damage is thought to be a good proxy for lack of fitness, it has been shown to be negatively associated with plant growth and seed production [1]. However, collecting and processing leaves is a laborious process that is hard to scale. To address this issue, we seek to develop automated methods to assess leaf damage by scaling traditional lab-based methods and creating new in-situ techniques. These techniques will help us compare the damage caused by different agents and better evaluate the effectiveness of Biocontrols.

Research Question

We would be interested in exploring the following questions :

Can we effectively measure plant damage from *in-situ* images alone through a deep learning-based computer vision analysis pipeline ? Our first (and most ambitious) question, aims at measuring plant damage directly from images captured in the field. Currently, the impact of biocontrols on invasive plant distribution, health and growth is generally assessed almost solely by collecting leaf/fruit samples in the field, which are then brought in a lab facility to measure how damaged they are through a tightly controlled protocol. This two-step process is very costly and represents a considerable limitation to the granularity of information you can hope to obtain from this type of study. If we are able to measure the damage inflicted on invasive plants by biocontrol agents through a deep learning-based computer vision pipeline that only requires plant images captured in the field as an input, it would allow the conservationists in Hawaii to monitor the progress and success of biocontrol experiments.

Can we improve *ex-situ* measurement protocols of plant damage through a deep learning-based computer vision analysis pipeline? Plant damage is usually measured *ex-situ*, in a laboratory-controlled setting where field samples (such as damaged leaves or fruits, see figure 1) are measured from images through a very strict protocol. This task is a very tedious process for our collaborators, and they would greatly benefit from having a tool that could automatically and accurately measure the damage ratio of their lab samples, instead of having to rely on a protocol that requires the validation of an expert for each sample. We will try to develop a deep learning-based computer vision pipeline that will automate the measurements of these lab samples, which will greatly improve the efficiency of our collaborators.

(a) (b)

Figure 1: (a) Lab-controlled picture of leaves (Credit : Ellyn Bitume) (b) Lab-controlled picture of *C. Hirta* fruits at different stages [4]

Dataset and Fieldwork Approach

We will study the damage done to*C. hirta* leaves by biocontrol agents in 19 points along 3 transects on the east side of the island of Hawaii [4]. Transects were selected from an altitude gradient ranging from sea level to more than 1000 meters in elevation, and were used in previous biocontrol studies of *Clidemia Hirta* in Hawaii [4]. For the pilot study, on each site, *Clidemia hirta* leaves will be collected with 3 visible levels of damage: **high**, **moderate**, and no-visible **damage**. Before collection, photos will be taken *in-situ* against a measurement plate. These leaves will be taken to the lab for processing, establishing the ground truth damage by traditional methods, and taking high-quality pictures for training the main model.

In order to answer our research questions and train our machine learning models, we will have to collect a dataset in the field. This dataset will contain the following elements :

- ***In-situ* images of native and invasive plants :** Which will be used to answer our first question.
- ***Ex-situ* images of damaged leaves :** Which will be used to answer our first and second questions.

The fieldwork protocol we are planning to use to build our dataset, is illustrated in figure 2, is made of four sequential steps :

1. **Take *in-situ* pictures of damaged plants :** Photos of leaves of *Clidemia hirta* and native plants will be taken with cell phones against a standardized measurement plate before collection.
2. **Collect damaged leaves (and potentially other relevant damaged parts of the plants, if needed) :** We will collect the damaged leaves of the plants we photographed during step 1, and potentially other biologically relevant parts of the plants as well (such as damaged fruits).
3. **Bring field samples to Ellyn's lab facility :** We will bring the field samples to Ellyn Bitume's lab facility, at the Pacific Southwest Research Station in Hilo. It is close to the Puʻu Makaʻala Reserve.
4. **Take pictures of the leaves with respect to Ellyn's protocol :** We will take pictures of the leaves (and potentially other parts of the plants as well) according to Ellyn's protocol, and take precise measurements of the damage from those images afterwards. These measurements will be used as *ground truths*, for both of our research questions.

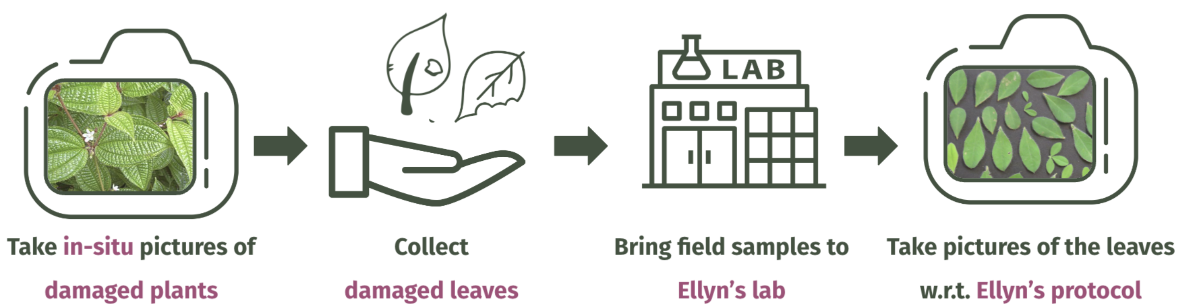

Figure 2: Illustrated summary of our field work data collection protocol

Methodology

We are planning to develop a **hybrid methodology** that combines **few-shot localization** and **zero-shot segmentation** to **detect and quantify plant damage**. Our proposed machine learning pipeline is summarized in Figure 3.

Figure 3: Illustrated summary of our proposed machine learning pipeline to automatically detect and quantify plant damage from images

Part 1 : Coarser damage segmentation module

The first part of our pipeline will consist of a **coarser segmentation module**, that will identify the broader regions of the plants in the images where the presence of damage is likely. We will notably experiment with the Grounding DINO model [10], that can generate bounding boxes over objects or regions of interest in images based on natural language descriptions, which makes it suitable for situations where specific annotations are scarce. The ability of Grounding DINO to identify regions of interest with natural language descriptions makes it notably suitable for tasks where domain knowledge from experts can be explained in clear textual descriptions, which will be our case since we will able to work on prompts with our biologist collaborators. Labeling and manually segmenting each damaged region of a plant in an image is significantly more time-intensive than leveraging domain-specific expertise to textually describe different types of plant damage.

By successfully integrating Grounding DINO, the efficiency of our pipeline could be greatly improved compared to the use of other conventional region segmentation methods such as YOLO v2 [15], the state-of-art object detection model that relies on image inputs only. If Grounding DINO doesn't work as well as expected, we could finetune the pre-trained YOLOv2 model to our task-specific requirements. This will however require that we label hundreds/thousands of images by hand, which could potentially limit our ability to succesfully experiment with YOLOv2.

Part 2 : Fine-grained damage segmentation module

While Grounding DINO and/or YOLOv2 could detect broad regions of interest, their ability to handle small, detailed, or fine-grained damage in leaves (or other plant parts of interest) may be limited due to their general-purpose, coarse-grained nature. They may struggle to detect subtle variations in plant damage, especially when the damage is localized to small portions. To refine the localization of damaged regions, we propose leverage SAM-v2 (Segment Anything Model) [14].

SAM-v2 excels at generating detailed segmentation masks when given spatial prompts. Bounding boxes produced by Grounding DINO (or YOLOv2) will serve as spatial prompts to guide SAM-v2 toward the damaged regions. SAM-v2 should provide us with fine-grained segmentation masks, which could allow us to obtain precise, pixel-level delineations from which we could estimate the damage ratios of the plants.

Although SAM-v2 may have the potential to provide us with highly accurate segmentations, its performance will be heavily influenced by the quality of the initial coarser localizations. If the bounding boxes provided by Grounding DINO and/or YOLOv2 are imprecise or overly broad, SAM-v2 will be much less effective in capturing the true extent of plant damage.

Baselines
We are currently aiming at comparing our pipeline to the following :

- **Ground truths :** We will take precise measurements of plant damage from lab-controlled images to use as ground truths
- **Ellyn's semi-automated ImageJ pipeline :** Ellyn Bitume, our biologist collaborator in Hawaii, currently uses a semi-automated pipeline implemented in the ImageJ software platform to estimate plant damage from lab-controlled images. We would like to improve the efficiency and accuracy of that approach.
- **A novel GAN algorithm :** A relevant GAN (**G**enerative **A**dversarial **N**etwork) algorithm was recently published in Methods in Ecology and Evolution [19]. This model tries to reconstruct a healthy leaf from a damaged leaf image in order to estimate the damage ratio.

Project Goals and Impact

To successfully develop novel tooling for in-situ plant damage assessment, and improve upon existing ex-situ methods, our project aims to complete the following goals: create methodology for in-the-wild image captures of invasive plants for the purpose of damage assessment, employ said methodology to create an in-situ plant damage dataset, following existing protocols to creat an ex-situ plant damage dataset, develop a novel processing pipeline utilizing state-of-the-art (SOTA) computer vision AI to accurately measure plant damage for both in-situ and ex-situ images, and deliver a friendly user-interface to our processing pipeline for maximum adaptation for end-users.

Upon completion of our targeted goals, our project aims to have the following machine learning impact: improved fine-grained segmentation of leaf damage measurement, novel utilization and adaptation of SOTA computer vision foundational models on leaf damage measurement, and a proposed few-shot training strategy for high performance with low annotation cost. Our project aims to have the following ecological impact: novel in-situ leaf damage quantitative measurement method, increased efficiency and scale of ex-situ leaf damage quantitative measurement methods, and provide a biocontrol agent impact analysis after release on target and (non-target) native species.

Further works

The goal of this study is the development of algorithms and methods for improving leaf damage assessment. An immediate application of the developed methods is to evaluate the effects of different biocontrol agents on curbing the spread of *Clidemia Hirta* over different attitude gradients. Altitude has been shown to be a limiting factor in the success of biocontrol agents. Our data collection strategy is designed to give us pilot data for future studies in that direction. One of the advantages of deep learning based methods is that they can be easily adapted to new contexts given the availability of training data, and with our few-shot training strategy, we aim to alleviate this collection process. Another potential application is to expand the scope of the project to include other invasive species and their potential biocontrol agents.

Other recent works evaluate the use of other agents such as the moths *Mompha Trithalama* and *Carposina Bullata* to control the spread of the invasive plant *Clidemia Hirta* [5]. They currently estimate the distribution of these moths in Hawaian forests through transects, and they measure their damage impact by first bringing damaged plant samples in the lab, and then by verifying if these damages are caused by moth larvae. We could for example try to improve the efficiency of this methodology by releasing moth camera traps in the field instead, notably by taking inspiration from the AMI (**A**utomated **M**onitoring of **I**nsects) system [16]. The AMI camera trap system was successfully released in the rainforests of Panama to enable the automated long-term monitoring of nocturnal insects, and a machine learning model able to identify thousands of different moth species from a dataset built with AMI images was recently released [8]. We could deploy a similar insect trap system in Hawaii, which would potentially allow us to assess the distribution of biocontrol agents from images instead of through transects.

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